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Los Alamos
NATIONAL LABORATORY

Deep learning to help find continuous gravitational waves

LANL Prism LGBTQ+STEM Day 2021

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2021 November 18 (JD 2459537)

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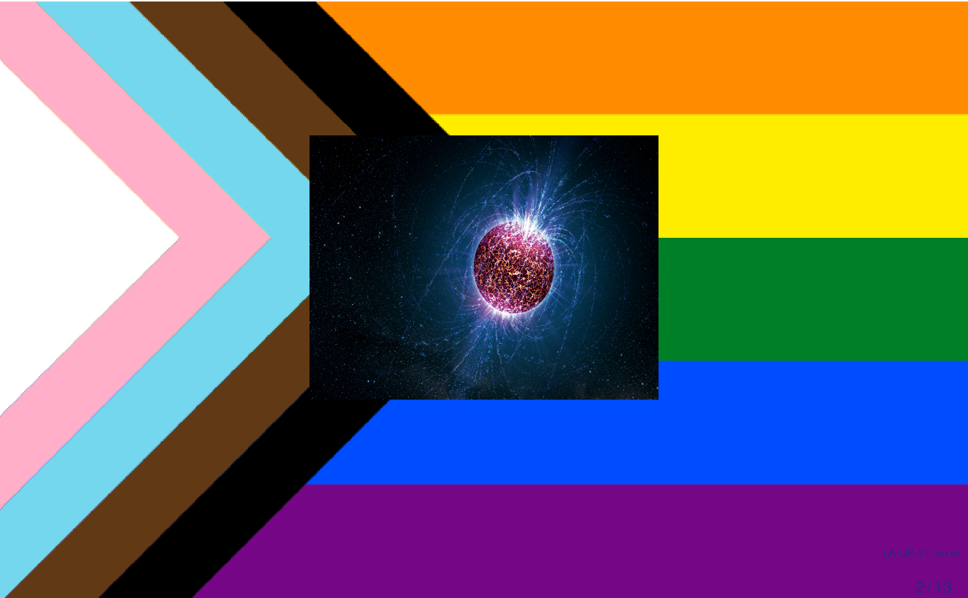
LGBTQ+STEM Day

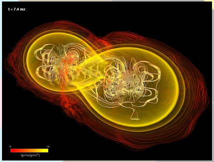
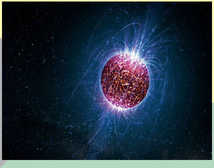
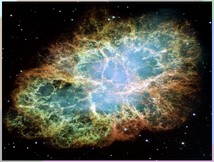
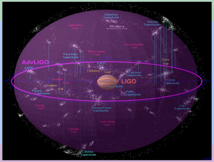


LGBTQ+STEM Day

Happy LGBTQ+STEM Day!

Today's talk is a celebration of research
that I (GDM) mentored this summer: the hard work
was done by my students (S. Goldhaber-Gordon & L. Smith)
at the ICR in Santa Fe, July 2021

What is a Gravitational Wave (GW)?

	Transient	*Persistent*
Modeled	 Coalescence	 Continuous $\leftarrow$
Unmodeled	 Burst	 Stochastic

Credits: AEI, Penn State (C. Reed), NASA, LIGO (B. Berger)

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Forward

Inspiration:
simulated data
convolutional neural net (CNN)
to help find
continuous-wave (CW)
[as-yet unseen]
gravitational waves (GWs)
believed to come from
neutron stars
in our galaxy

PAPERS

- Dreissgacker, Sharma, Messenger, Zhao, Prix
  Deep-learning continuous gravitational waves, Physical Review D, **100**, 044009 (2019)
- Dreissigacker & Prix,
  Deep-learning continuous gravitational waves: multiple detectors and realistic noise, Physical Review D, **102**, 022005 (2020)

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Forward

PHYSICAL REVIEW D **100,** 044009 (2019)

Deep-learning continuous gravitational waves

Christoph Dreissigacker,[1,2,*] Rahul Sharma,[3,1,2] Chris Messenger,[4] Ruining Zhao,[5,6,7] and Reinhard Prix[1,2]
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(Received 6 May 2019; published 7 August 2019)

We present a first proof-of-principle study for using deep neural networks (DNNs) as a novel search method for continuous gravitational waves (CWs) from unknown spinning neutron stars. The sensitivity of current wide-parameter-space CW searches is limited by the available computing power, which makes neural networks an interesting alternative to investigate, as they are extremely fast once trained and have recently been shown to rival the sensitivity of matched filtering for black-hole merger signals [D. George and E. A. Huerta, Phys. Rev. D **97**, 044039 (2018); H. Gabbard, M. Williams, F. Hayes, and C. Messenger, Phys. Rev. Lett. **120**, 141103 (2018)]. We train a convolutional neural network with residual (shortcut) connections and compare its detection power to that of a fully coherent matched-filtering search using the WEAVE pipeline [K. Wette, S. Walsh, R. Prix, and M. A. Papa, Phys. Rev. D **97**, 123016 (2018)]. As test benchmarks we consider two types of all-sky searches over the frequency range from 20 to 1000 Hz: an "easy" search using $T = 10^5$ s of data, and a "harder" search using $T = 10^6$ s. The detection probability p_{det} is measured on a signal population for which matched filtering achieves $p_{\text{det}} = 90\%$ in Gaussian noise. In the easiest test case ($T = 10^5$ s at 20 Hz) the DNN achieves $p_{\text{det}} \sim 88\%$, corresponding to a loss in sensitivity depth of $\sim 5\%$ versus coherent matched filtering. However, at higher frequencies and for longer observation times the DNN detection power decreases, until $p_{\text{det}} \sim 13\%$ and a loss of $\sim 66\%$ in sensitivity depth in the hardest case ($T = 10^6$ s at 1000 Hz). We study the DNN generalization ability by testing on signals of different frequencies, spindowns and signal strengths than they were trained on. We observe excellent generalization: only five networks, each trained at a different frequency, would be able to cover the whole frequency range of the search.

DOI: 10.1103/PhysRevD.100.044009

PHYSICAL REVIEW D **102,** 022005 (2020)

Deep-learning continuous gravitational waves: Multiple detectors and realistic noise

Christoph Dreissigacker[*] and Reinhard Prix
Max Planck Institute for Gravitational Physics (Albert-Einstein-Institute), D-30167 Hannover, Germany and Leibniz Universität Hannover, D-30167 Hannover, Germany

(Received 11 May 2020; accepted 17 June 2020; published 6 July 2020)

The sensitivity of wide-parameter-space searches for continuous gravitational waves is limited by computational cost. Recently it was shown that deep neural networks (DNNs) can perform all-sky searches directly on (single-detector) strain data [C. Dreissigacker *et al.*, Phys. Rev. D **100**, 044009 (2019)], potentially providing a low-computing-cost search method that could lead to a better overall sensitivity. Here we expand on this study in two respects: (i) using (simulated) strain data from two detectors simultaneously, and (ii) training for directed (i.e., single sky-position) searches in addition to all-sky searches. For a data time span of $T = 10^5$ s, the all-sky two-detector DNN is about 7% less sensitive (in amplitude h_0) at low frequency ($f = 20$ Hz), and about 51% less sensitive at high frequency ($f = 1000$ Hz) compared to fully-coherent matched-filtering (using WEAVE). In the directed case the sensitivity gap compared to matched-filtering ranges from about 7%–14% at $f = 20$ Hz to about 37%–49% at $f = 1500$ Hz. Furthermore we assess the DNN's ability to generalize in signal frequency, spin down and sky-position, and we test its robustness to realistic data conditions, namely gaps in the data and using real LIGO detector noise. We find that the DNN performance is not adversely affected by gaps in the test data or by using a relatively undisturbed band of LIGO detector data instead of Gaussian noise. However, when using a more disturbed LIGO band for the tests, the DNN's detection performance is substantially degraded due to the increase in false alarms, as expected.

DOI: 10.1103/PhysRevD.102.022005

Introduction

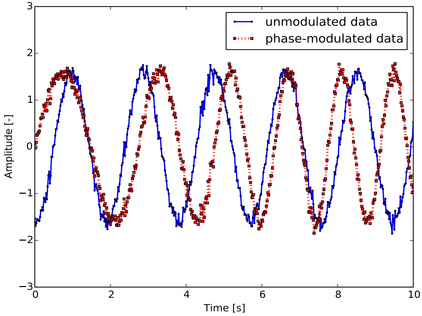
These papers are neat!
Potentially-robust and fast way
to handle what's been
a Petascale computing challenge!

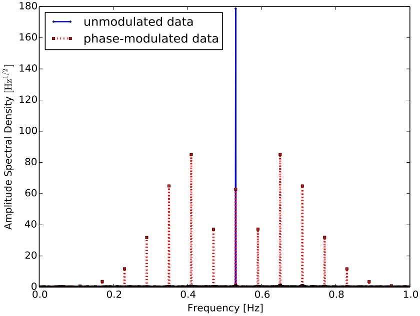
Puzzle: loss of sensitivity at high frequency
(possibly because of Doppler effects?)

Could CNNs help us finally see CWs?
Let's find out!

How does a Continuous Wave (CW) look?

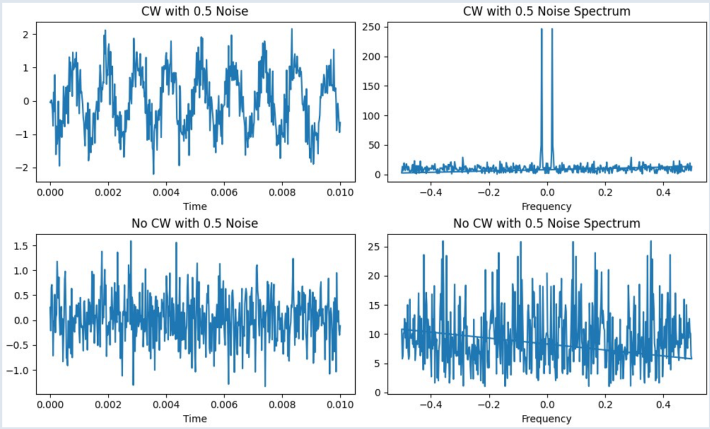
Phase modulation in long-duration GWs (simplified illustration)





Roemer/Doppler effect from orbit in time & Fourier domains

Student work: simulating data



(UL) time-domain noise+signal, (UR) frequency-domain noise+signal
(LL) time-domain noise only, (LR) frequency-domain noise only
simulated increasing noise levels (lower SNR)

Student work: neural net architecture

```
model = tf.keras.Sequential([
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(2)
])
```

Six dense layers: ‘convolutional’ may be misnomer,
but it trains! Layers sized to match time-series duration.
Final output: **detection** or **not**?

Student work: neural net training

```python
model.compile(optimizer='adam',
   loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
   metrics=['accuracy'])

model.fit(np.abs(np.fft.fft(training_data)), training_labels, epochs=15)
```

Note: intake is fft

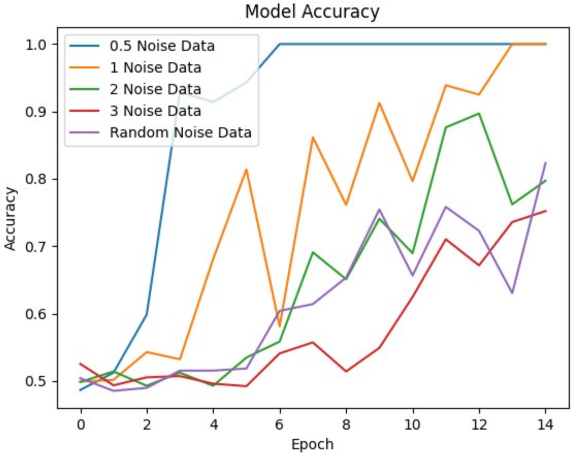
```python
test_loss, test_acc = model.evaluate(np.abs(np.fft.fft(testing_data)), testing_labels, verbose
print('\nTest accuracy:', test_acc)

probability_model = tf.keras.Sequential([model, tf.keras.layers.Softmax()])
predictions = probability_model.predict(testing_data)
print(predictions[0])
print(np.argmax(predictions[0]))
print(testing_labels[0])
```

Training on FFT data offloads heavy lifting.

Students shared their code w/ Github (none mine; based on MNIST tutorial)

no prior ML experience → `Jupyter` notebooks *written in 4 weeks*

Student work: training history in noisy data



Model trains on *accuracy* metric in few epochs, hours on laptop:
longer, more realistic data present way forward (papers used clusters)

Conclusion

- CNNs potentially a way to find CW gravitational waves
- `TensorFlow` accessible to high-school students
- Lots left to do,
  implementing realistic phase modulation,
  explore loss of sensitivity at high-frequency,
- **Proof-of-concept** – ML on frequency (Fourier) domain
  success!

Acknowledgments
Thanks to Prism for hosting this talk, to Mark Galassi & Rhonda Crespo of the Institute for Computing in Research (Santa Fe) for inviting me to be a mentor,
to Pride in STEM for starting LGBTQ+STEM Day
+ you for your attention!

Questions: gdmeadors@lanl.gov